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Fine-Tuning Localization and Navigation Parameters for Accurate Greenhouse Mapping

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Abstract: Accurate mapping is crucial for maximizing productivity and sustainability in agriculture. However, creating maps in greenhouse environments is challenging due to their intricate layouts, often resulting in bending and reduced precision. To address these challenges, fine-tuning was applied to the parameters of the Simultaneous Localization and Mapping (SLAM) algorithm and the navigation process, specifically focusing on the Grid-based Mapping (GMapping) and Dynamic Window Approach (DWA) techniques. SLAM experiments were conducted in a simulated greenhouse environment created by Gazebo, with all operations executed under the Robot Operating System (ROS) framework, enabling real-time mapping and localization. Comparisons between maps generated with and without fine-tuning, and the Gazebo reference map, show a 77.8% improvement in reducing map distortion, resulting in more precise greenhouse representations. These findings highlight how the fine-tuning of algorithm parameters can improve mapping accuracy, ultimately enhancing agricultural applications. Future work will focus on testing this methodology to ensure broader applicability and reliability in real-world greenhouse environments.

Keywords: Agriculture, Greenhouse Environments, Mapping, Robotics, SLAM

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1. INTRODUCTION

In modern agriculture, the accurate mapping of agricultural environments is essential for maximizing productivity and sustainability [1]. Precision mapping enables efficient resource utilization and targeted interventions, leading to optimized crop management practices [2]. However, creating precise maps of agricultural landscapes, particularly in greenhouses, presents significant challenges due to their intricate layouts and limited accessibility [3]. These issues can cause map bending and inaccuracies, compromising the effectiveness of agricultural applications that rely on precise mapping [4]. Existing mapping techniques, including Global Position System (GPS), aerial imagery, and simulated maps, often struggle to provide the level of detail required for precise navigation and monitoring within these environments [2, 5, 6].

An alternative to these traditional methods is Simultaneous Localization and Mapping (SLAM). SLAM is a robotics method for creating maps of an environment while simultaneously tracking the robot's location within it. It is classified into two principal approaches: Li-DAR SLAM, which relies on laser sensors, and Visual SLAM (V-SLAM), which utilizes cameras [7]. LiDAR-SLAM algorithms have evolved significantly, with Grid-based Mapping (GMapping) enhancing particle loss but relying heavily on odometry data [8]. Hector SLAM offers mapping precision without odometry reliance but faces initial sensitivity [9]. Despite advancements like Cartographer's improved detection, LiDAR-SLAM demands substantial computational resources [10].

Over the years, many advancements have been made in 2D LiDAR-based SLAM, demonstrating significant progress in creating accurate maps for autonomous navigation [3, 11-16]. However, most research has applied these algorithms in relatively simple environments with minimal obstacles. Addressing the limitations of current studies will lead to fine-tuning these algorithms, making them suitable for more complex environments and enhancing their effectiveness and reliability to be applied in agricultural applications.

This study proposes a methodology that fine-tunes the GMapping algorithm and the Dynamic Window Approach (DWA) to better suit the specific requirements and characteristics of greenhouse environments. SLAM operations will be conducted within a simulated greenhouse environment using Gazebo [17], a robotics simulation tool integrated with ROS (Robot Operating System) [18]. This approach allows for real-time mapping and localization, enabling the creation of detailed and precise maps of the greenhouse layout [4].

The subsequent sections of this paper are organized as follows: Section 2 provides a comprehensive overview of related studies to position the proposed approach within existing research. Section 3 outlines the methodology employed in this study. Following that, Section 4 presents the results and their significance. Finally, Section 5 concludes the paper with key insights and recommendations.

2. RELATED STUDIES

Real-time map generation through SLAM on mobile robots is pivotal for effective navigation in complex environments [4]. Several algorithms have been developed to enhance SLAM performance in indoor environments using LiDAR sensors. Cartographer has demonstrated high precision in static settings with TurtleBot2 and LiDAR [11], while GMapping has proven effective for simulation-based mapping using laser and odometry data [12]. Advanced approaches, such as the enhanced Rao-Blackwellized Particle Filter SLAM (LRBPF-SLAM), further improve pose estimation and map construction [13].

In agriculture, SLAM algorithms have been applied to enhance monitoring and navigation. For example, the BFS algorithm on TurtleBot3 has been used for autonomous frontier exploration, improving mapping and obstacle detection [15]. GMapping has also been employed for robot localization in controlled agricultural environments, but its limitations in larger and more complex areas remain a challenge [3]. A study by [16] highlighted the benefits of systematically fine-tuning GMapping parameters to improve SLAM performance, achieving significant map accuracy in structured indoor environments. Additionally, a navigation system tailored for indoor substations integrates hardware and sensors with ROS, enhancing navigation precision and robustness [13,14]. Despite advancements in the literature, much of the focus has been on simple environments or algorithm implementation, leaving a critical gap that emphasizes the need for fine-tuning to achieve accurate mapping amidst the intricate layouts and unique challenges of greenhouse environments.

3. METHODOLOGY

This section details the procedures and algorithms employed to address the SLAM process in agricultural robotics. The techniques and strategies used to create the Occupancy Grid Map (OGM) via the RViz tool, based on the ROS framework [19], are outlined in Algorithm 1. The generation of an OGM through RViz is a critical component of this study, providing a digital representation of the environment that enables effective robotic navigation and precise localization The map utilized in this study spans dimensions of 9.3 meters in width and 15.7 meters in length, encompassing intricate layouts typical of greenhouse environments.

To address the issue of map bending, the study focused on fine-tuning both the GMapping SLAM algorithm parameters and the DWA navigation parameters. Building on insights from [16], which emphasized the impact of parameter fine-tuning on SLAM performance, specific GMapping parameters were tuned. These included translation errors (srr and srt), rotation errors (str and stt) and $particles$, which are known to influence pose estimation and map accuracy in spatially constrained environments like greenhouses.

Guided by [20], DWA parameters responsible for odometry errors, including maximum and minimum angular velocities (max_vel_theta and min_vel_theta), acceleration limits for both linear and angular velocities (acc_lim_x and acc_lim_theta), number of velocity samples ($vx\_samples$) and the $path\_distance\_bias$, were carefully considered to improve trajectory stability and enhance overall SLAM reliability.

The methodology presented in Algorithm 1 adopts an iterative process, combining simulation results, RViz visual inspection, and ImageJ analysis [21] to assess and improve map quality. During the fine-tuning process, RViz's global map overlay is used to evaluate map bending and alignment issues. Once the fine-tuning process achieves satisfactory results, ImageJ software is employed in the post-fine-tuning analysis stage. ImageJ facilitates detailed structural and quantitative evaluation, including steps such as grayscale conversion, Gaussian blur filtering, and histogram equalization. These preprocessing steps enhance visualization and comparability of the maps, ensuring consistent preparation for advanced analysis.

Algorithm 1. Setting up the robot environment and fine-tuning

1: **procedure** $simulation\ environment$
2: Initialize ROS nodes
3: Launch Gazebo simulation with robot model
4: Launch RViz visualization tool
5: **Fine-tuning process:**
6: Fine-tune GMapping parameters
7: Fine-tune DWA parameters
8: Generate a new OGM
9: Evaluate the generated OGM visually in RViz using the global map overlay for bending, alignment, and structural consistency
10: If necessary, repeat Steps 5–9 to refine the parameters further
11: **end fine-tuning**
12: **Post-fine-tuning analysis:**
13: Finalize the OGM after satisfactory results
14: Perform detailed structural and quantitative evaluation using ImageJ for bending metrics, correlation, and intensity profiles
15: **end post fine-tuning**
16: **end procedure**

3.1 ROS and Gazebo Simulation Setup

The proposed simulation environment is built upon ROS Noetic Ninjemys, operating on Linux Ubuntu 20.04 with a hardware setup featuring Intel Core i5 13th generation CPU and 16 GB of RAM. In this environment, $roscoe$ command initiates the parameter server, while $roslaunch$ manages node configurations [18]. Gazebo complements ROS by offering a dedicated 3D simulation space tailored for greenhouse environments, facilitating development and testing [17]. Figure 1 presents a detailed visual representation, showcasing a 3D view of the simulated greenhouse with approximately 250 saplings.

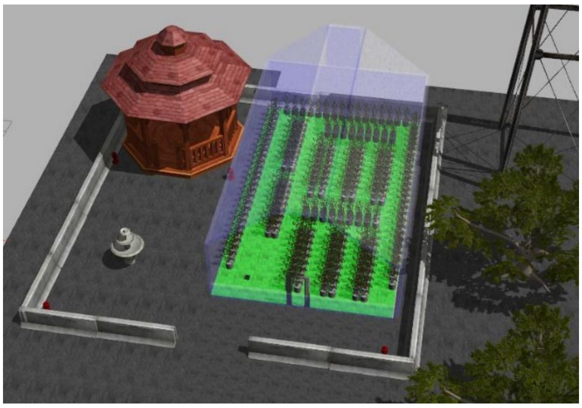


Figure 1. Simulated greenhouse environments in Gazebo

3.2 OGM Map Creation

The GMapping algorithm is employed for SLAM, renowned for its efficiency in indoor settings, especially with a 2D laser sensor. Concurrently, DWA algorithm, available as a ROS package $dwa\_local\_planner$ [20], is utilized for enhanced navigation. In the GMapping algorithm, the creation of a map relies on OGM, where each cell represents free space, occupied space, or unknown space. The probability of a sensor measurement z_t at time t given the map m and the robot's pose x_t is computed using sensor models like $P(z_t|m, x_t)$. This equation, along with the robot's pose estimation, aids in evaluating how well each particle aligns with the sensor data. Furthermore, the importance weight w_t^i of each particle i at time t is determined by $P\left(z_t|x_t^i, m\right)$, indicating its agreement with the sensor measurements. Higher weights lead to replication during resampling, directing the filter towards more probable robot poses. Map updates are executed based on sensor data, employing techniques such as ray casting for lidar-like sensors and inverse sensor models for occupancy grid sensors [8].

Navigation points are specified in RViz using the "2D NAV Goal" tool, directing the robot to traverse and accumulate map data. This process involves setting multiple points to ensure a thorough mapping of the entire area. After completing the SLAM operation the map data is saved using the command $rosrun\ map\_server\ map\_saver - f\ \ \sim/map\_name$, resulting in the map being stored in the package's map directory as $map\_name.pgm$.

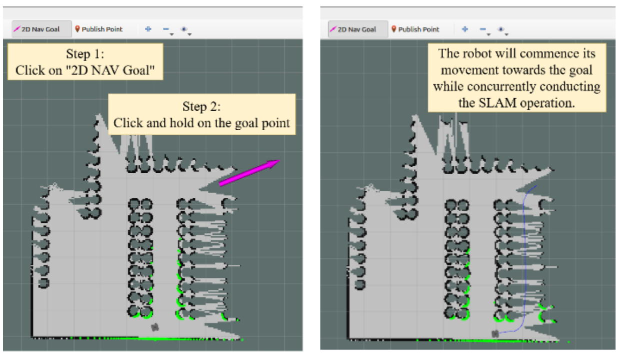


Figure 2. SLAM process in RViz using GMapping and DWA algorithms

Launching the SLAM process in the robotic simulation involves executing several components and configurations. This includes initiating ROS, launching the $greenhouse\_world.launch$ and $turtlebot3\_remote.launch$ files, setting up the Universal Robot Description Format (URDF) model of the Turtlebot3 [20], starting the map_server, launching the $turtlebot3\_gmapping.launch$ file, initiating the move_base node, and opening RViz for simulation visualization. Figure 2 shows the SLAM process in RViz, employed by the GMapping and DWA algorithms.

4. RESULTS AND DISCUSSIONS

This study examined the impact of fine-tuning SLAM and navigation parameters on indoor greenhouse mapping accuracy, focusing on addressing the map bending issue by refining GMapping and DWA parameters. For GMapping, the fine-tuning targeted odometry error parameters ($srr, srt, str,$ and stt) and particle count. Fine-tuning these parameters enhanced pose estimation and map accuracy, as summarized in Table 1. The refined odometry parameters mitigated translation and rotation inaccuracies, while increasing the particle count to 1000 improved localization robustness, ensuring reliable mapping in the intricate layouts typical of greenhouse environments.

Table 1. GMapping default and fine-tuned parameters used in the experiment

Parameter	Default values (wiki.ros.org/gmapping)	Fine-tuned values
srr	0.1	0.0001
srt	0.2	0.0002
str	0.1	0.0001
stt	0.2	0.0002
$particles$	30	1000

Similarly, the DWA parameters were iteratively fine-tuned to overcome navigation challenges specific to the greenhouse environment. As shown in Table 2, angular velocity limits (max_vel_theta and min_vel_theta) were fine-tuned to ensure controlled rotational movements, which are essential for maintaining stable trajectories in narrow aisles. Acceleration limits (acc_lim_x and acc_lim_theta) were refined to achieve smoother transitions, minimizing jerky movements that could exacerbate odometry errors. The velocity sampling ($vx\_samples$) was reduced to strike a balance between computational efficiency and trajectory planning accuracy, while the path distance bias was increased to prioritize adherence to planned paths, enhancing mapping consistency. These parameter fine-tuning efforts were specifically tailored to address the unique challenges, building upon the practical considerations outlined in the methodology.

Table 2. DWA default and fine-tuned parameters used in experiment

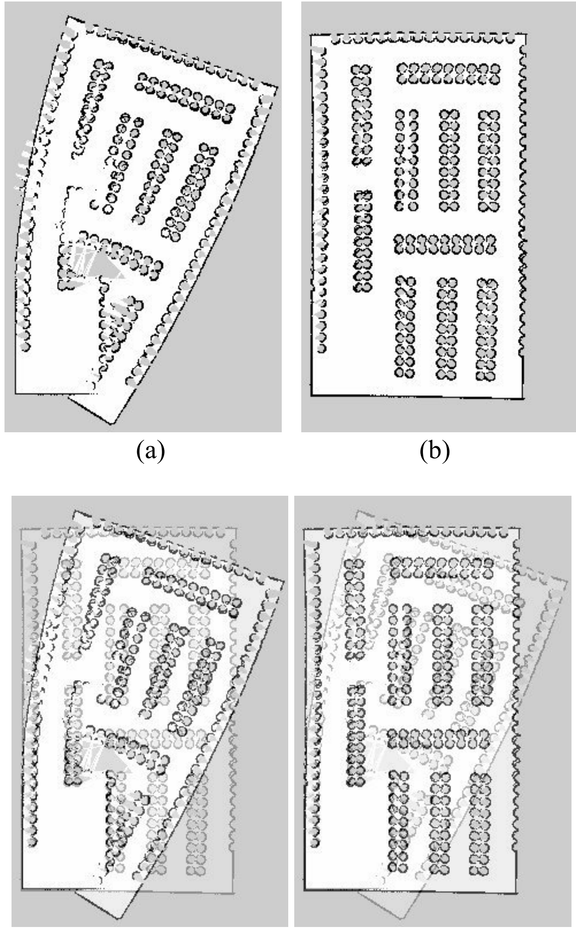
Parameter	Default values (wiki.ros.org/dwa_local_planner)	Fine-tuned values
max_vel_theta (rad/sec)	1.0	0.32
min_vel_theta (rad/sec)	1.0	0.12
acc_lim_x (m/s²)	2.5	0.52
acc_lim_y (m/s²)	25	0.0
acc_lim_theta (rad/s²)	3.2	1.2
$vx\_samples$	3	10
$path\_distance\_bias$	32.0	72.0

A visual comparison provides clear evidence of the improvements achieved through fine-tuning. Figure 3 highlights the differences between the distorted map (Figure 3 (a)) and the fine-tuned map (Figure 3 (b)), showcasing the impact of parameter fine-tuning on map accuracy and structural coherence.

To highlight these differences more clearly, ImageJ was utilized to create overlays [21]. The fine-tuned map, superimposed at 30% opacity onto the distorted map, highlights the rectified regions and improved alignment, while the distorted map, overlaid onto the fine-tuned map at the same opacity, accentuates the misalignments and irregularities caused by the default parameters (Figure 3 (c) and Figure 3 (d)). Together, these visual analyses effectively validate the enhancements achieved through the fine-tuning process, particularly in reducing map bending and improving feature alignment.

For further analysis, preprocessing steps were performed using the same software to prepare the maps for quantitative evaluation. The ground truth map (Gazebo map), shown in Figure 4 (a), was converted from its original-colored format to grayscale to ensure consistency with the fine-tuned and distorted maps. Shadows and non-uniform lighting in the Gazebo map underscored the need for robust preprocessing. All maps were then converted to binary format to simplify pixel intensity comparisons and highlight structural features. A Gaussian blur filter (σ=6) was applied to reduce noise and smooth intensity transitions while preserving structural integrity. Histogram equalization followed, redistributing pixel intensities across the full range to enhance contrast and uniformity. The results are shown in Figure 4 (b) for the Gazebo map, Figure 4 (c) for the fine-tuned map, and Figure 4 (d) for the distorted map, facilitating statistical analysis and intensity profile comparisons.

The correlation analysis quantified the alignment between the maps, with the fine-tuned map exhibiting a strong correlation coefficient (r=0.889) with the Gazebo map, validating the fine-tuning process. In contrast, the distorted map showed moderate correlations with both the Gazebo map (r=0.500) and the fine-tuned map (r=0.454), emphasizing the improvements achieved through parameter adjustments.



(a) (b) (c) (d)

Figure 3. (a) Distorted map with default parameters, (b) fine-tuned map, (c) fine-tuned map overlaid on distorted map and (d) distorted map overlaid on fine-tuned map

Figure 5 further illustrates these findings through intensity profiles of the Gazebo, fine-tuned, and distorted maps. The fine-tuned map closely follows the intensity trends of the Gazebo map, reflecting improved alignment and rectification of structural irregularities. Conversely, the distorted map demonstrates significant deviations, particularly in complex regions, highlighting the limitations of the default parameters. Combined, the correlation analysis and line plot confirm the effectiveness of fine-tuning in enhancing map quality and alignment with the ground truth.

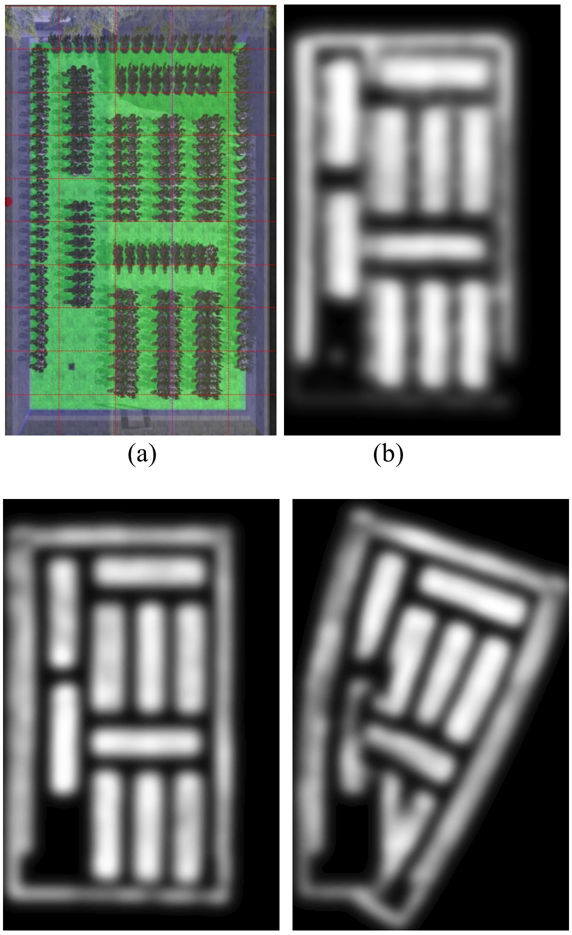


Figure 4. (a) Original colored Gazebo map; preprocessed maps: (b) Gazebo, (c) Fine-tuned, and (d) Distorted.

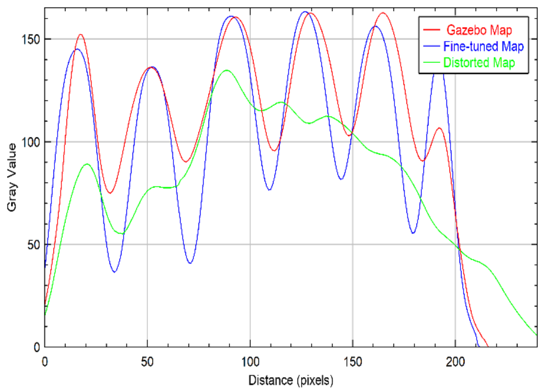


Figure 5. Intensity profiles of Gazebo, fine-tuned, and distorted maps

5. CONCLUSION

The fine-tuning of GMapping and DWA parameters significantly enhanced the accuracy and reliability of indoor greenhouse mapping. Visual and statistical analyses, including overlays and line plots, demonstrated the improved structural alignment and intensity consistency achieved through fine-tuning. Quantitative analysis revealed a 77.8% improvement in alignment between the fine-tuned map and the ground truth (Gazebo map) compared to the distorted map. These results highlight the effectiveness of fine-tuning in addressing map bending and alignment inconsistencies, leading to a more precise and reliable environmental representation. Future work could focus on validating this methodology in real-world greenhouse environments to ensure its broader applicability and effectiveness in complex agricultural scenarios.

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